Stereo Matching Technique using Belief Propagation

Annual Progress Seminar Report-III

Ph.D.

(Electronics Engineering)

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Abstract

The stereoscopic images or stereo pair consists of two images of the same scene taken slightly horizontally separated points from the left view and the right view. The parallax effect also present in stereoscopic images in such a way that objects near the camera will represent more to the right in the left image and more left in the right image. The horizontal displacement of an object left and right view depends on the distance from the object to the camera view points.

To find the matching pixel in left and right image for stereo pair image is known as **Stereo** Vision, **Stereo Correspondence Or Stereo Matching**.

In stereo matching aim is to find the matching pixel for a stereo pair image as input image which consists of left and right image and result of finding matching pixel is saved as Depth map or disparity map. The disparity is horizontal distance between two matching pixel and horizontal pixel distance for each pixel coordinates is nothing but Disparity map.

The Global algorithms are based on Bayesian approach finds disparity as an energy minimization problem. The Global stereo algorithms are Graph cut and belief propagation. Keywords:Probability theory,Markov Random Field and Belief Propagation

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Introduction

A parallax is ability to see an object at two different views. Parallax is a difference in the observable position of an object viewed along the two different lines of sight and is measured by an angle between those lines.

As an illustration for parallax is that, as we know that earth revolves around the sun every year, earth takes its position opposite side of the sun every six months because of parallax effect nearby stars will seems to move relative distance than faraway stars. Another example for parallax effect is that hold a pencil at arm's length and look at it through one eye than other eye it looks like it shifts its position actually it not changes its position.

As another illustration how disparity can be appears is that by holding index finger one near to the face other as far as one can reach, on alternately viewing the scene with left eye and right eye. The distance between two fingers is different in left than in right eye which is due to relative position in two retinae are disparate.

Disparity is defined as the difference in the location of the object between right eye's and left eye's image. The amount of disparity depends on the depth. The depth is difference in distance to the two objects and distance to the point of fixation. Due to the parallax effect and human being's eye structure in such way that can see the objects in 3D depth. However the disparity also depends on distance to the fixation as well as disparity are interpreted as estimates of fixation of distance. The same principle is used while finding disparities for stereoscopic images

The stereoscopic images or stereo pair consists of two images of the same scene taken slightly horizontally separated points from the left view and the right view. The parallax effect also present in stereoscopic images in such a way that objects near the camera will represent more o the right in the left image and more left in the right image. The horizontal displacement of an object left and right view depends on the distance from the object to the camera view points.

To find the matching pixel in left and right image for stereo pair image is known as **stereo vision**, **stereo correspondence or stereo matching**. In stereo matching aim is to find the matching pixel for a stereo pair image as input image which consists of left and right image and result of finding matching pixel is saved as Depth map or disparity map. The disparity is horizontal distance between two matching pixel and horizontal pixel distance for each pixel coordinates is nothing but Disparity map.

The Depth map or Disparity map is a gray scale image which is highly compressed. The Depth map or Disparity map shows distance rather than texture. If shift of pixel between right and left stereo image is more than object looks darker which is located far away

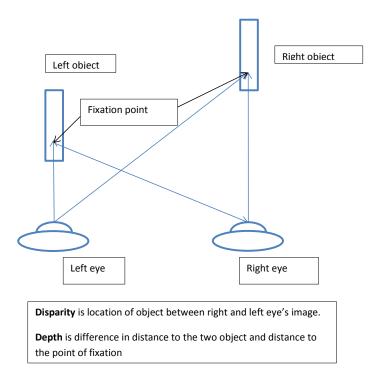


Figure 1.1: Conceptual diagram for Disparity

from camera and if shift is less than object is bright i.e. object close to the camera. Stereo matching Algorithm is classified as **Area-based**, **Feature-based and Global algorithm**.

- 1. The Area and feature based algorithms are based on intensity profile. The constrains in area- based algorithm is to find the optimal size of the window.
- 2. The feature-based algorithms are restricted to using only specific feature, that only yield sparse disparity maps.
- 3. The Global algorithms are based on Bayesian approach finds disparity as an energy minimization problem. The Global stereo algorithms are Graph cut and belief propagation.

Some applications of Depth Map or Disparity Map are

- To reconstruct 3D model sequences which can be used either for information transfer or for entertainment.
- For robot application for navigation purpose and for object recognition to separate occluded image components.
- Scientific application of Depth Map or Disparity Map are to extracts information from aerial surveys and for calculation of contour maps

• For Gaze correction for video conference and for Image sequence analysis

This report is organized as follows:

The Introduction to research work is discussed in chapter 1. Chapter 2 done Literature Survey to find gap analysis 3 Mathematical Representation of Global stereo Algorithm are explained. chapter 4 focuses on Implementation of Belief Propagation and chapter 5 presents the conclusion and future work.

Literature Survey

The major contribution in the field of stereo matching using Random Markov field and inference algorithm like Belief Propagation

[2003] Comparison of Graph cuts with Belief Propagation for stereo, Using Identical MRF Parameters:[1]

The disparity image can be achieved by modelling Markov Random Field and by using optimization algorithm such as Graph cut and Belief Propagation. These two algorithm allow fast and approximate solution to MRF which are powerful tools for modelling vision problems.so one system improvement over the other be attributed to its choice of an inference algorithm.

The comparison between Graph cut algorithm with max product Belief Propagation algorithm shows that the solution for energy by Graph cut and Belief Propagation algorithm nearly equal although graph cut consistently returns smaller energy. The solutions produced by Graph cut are smoother while accelerated Belief Propagation algorithm was faster.

Given this situation Improving formulation of MRF rather than improving solution (optimization algorithm) for MRF. The comparisons between inference algorithm such as Graph cut and Belief Propagation depends on the functions of MRF formulation.

The future research can be different functions such as truncated linear or quadratic used for MRF optimizing with any one of the inference algorithm[1]

[2004] Efficient Belief Propagation for Early Vision:[2]

The early vision problems such as stereo, optical flow and image restoration can be solved by MRF model by using inference algorithm based on Graph cut and Belief propagation In this paper new algorithm techniques improve the running time of the algorithm. The inference algorithm used is max product belief propagation.

The three techniques substantially reduces time required to compute the message updates.

- 1. In low level vision problems the label or hidden node is generally based on some difference between two labels rather than on particular pair of labels, this is known as distance transform technique. This technique reduces message computing time.
- 2. In new message update scheme, here nodes are split into two Messages are updated alternately ,so half of the messages only updated at each iteration.so memory required to store messages are reduced.
- 3. The third technique uses hierarchical structure to reduce the number of message passing iterations to small constant rather depends on size of the image grid.

[2007] Low Memory Cost Block Based Belief Propagation for Stereo Correspondence[3]

The global approaches can handle the texture less and occluded regions well by formulating disparity inference as an energy minimization problem. The energy functions usually has smoothness constraint which represents a certain relationship between neighboring pixel pair. This smoothness constraint enforces penalty on the energy function, if the labels (disparity or segments) of neighboring pixel are inconsistent.

The 2D optimization algorithm such as graph cut and Belief Propagation have been applies successfully to optimize energy functions. The BP algorithms construct 2-D graph structures with nodes represent all pixels in the disparity image to find the disparity map with energy closer to the global minima. However, the vast number of nodes in 2-D graph result in extremely high computation complexity too difficulty in real time applications. The proposed Block based Belief Propagation algorithm directly partitions image into separated independent blocks.so memory size reduces significantly due to block based computation. With block based design, the criterion of convergence becomes important for each block.

In general, the criterion of convergence in belief propagation is defined with the saturation of energy functions. The specific threshold is set to terminate the belief propagation process. However it is difficult to find a global threshold for each block. In proposed algorithm find the convergence according to the equivalence of all disparities for each node in a block over successive iterations.

[2009] Hardware-Efficient Belief Propagation[4]

Loopy belief propagation is an effective solution for assigning labels to the nodes of a graphical model such as Markov Random Field, but requires high memory, bandwidth and computational costs. In this paper two techniques are proposed

- 1. Tile based Belief propagation ,when message is updated data of nodes which are far away are not required, so MRF is divided into multiple regions known as tile and iterations are done on those regions. So memory required to store messages are reduced.
- 2. Fast message construction: The cost functions serve for measuring the compatibility between the labels and the observations or prior knowledge. For example in stereo matching that the disparity values vary smoothly between neighboring pixels. However this assumption is valid only when corresponding pixels belong to the same object. otherwise the difference between their disparity values can be arbitrarily large resulting high cost value. In fast message construction using robust function is used as smmothness cost.

Table 2.1: Optimization methods used for finding the disparity from various research papers

The summary of literature survey is mentioned in table

| Research pa- | Optimization Method | Scope for Research |
|--|---|--|
| per | | |
| Comparison of Graph cuts with Belief Propagation for stereo, Using Identical MRF Parameters [2003] | Comparative study of Graph cut and Belief Propagation on same MRF Model | Further study of Improving formulation of MRF rather than improving solution for MRF |
| Efficient Belief Propagation for Early Vision [2004] | Three methods are used 1. Distance transform technique(difference between two labels) 2. New message update scheme 3. Hierarchical structure | Further study can be: These optimization method can be applicable to a broad range of more sophisticated cost functions. |
| Low Memory Cost Block Based Belief Propagation for Stereo Correspondence [2007] | 2D BP Graph is divided into blocks. Optimize each block separately. | The information exchange between Neighboring fin- ished processing block and unfinished processing block can be further investigated |
| Hardware- Efficient Belief Propa- gation [2009] | Efficiency of BP is improved by new message scheme known as Tile based BP and Fast message construction | The performance Tile based message passing scheme can be studied for different con- ditions like different smooth- ness cost functions |

Mathematical Representation of Global stereo Algorithm

The stereo matching problem can be expressed as global function .The optimization technique used by this global function are by combining matching cost and smoothness cost terms and possibly other terms to get disparity map. Stereo matching problem can be interpreted in terms of probability theory as well as markov network.

3.1 Stereo matching in terms of Probability theory

The stereo matching problem can be expressed in terms of probability theory

- Let assume Y is stereo set and X is disparity map
- Probability of disparity map to stereo set is P(X/Y), Probability of disparity map is P(X) and Probability of stereo set is P(Y)
- According to Bays theorem from probability theory is

$$P(X/Y) = P(Y/X) * P(X)/P(Y)$$
 (3.1)

- Probability of stereo set i.e.P(Y) can made equal to 1
- Than

$$P(X/Y) = P(Y/X) * P(X)$$
(3.2)

The disparity map can be obtained by maximizing probability of disparity map to stereo set i.e. P(X/Y) and it can be possible by expressing probability into function.

3.1.1 Matching cost function

The probability of stereo set to disparity map i.e. P(Y/X) represents total matching cost across all pixels in stereo set. When probability of stereo set to disparity map i.e. P(Y/X) is low than total matching cost is more and viceversa.

Therefore probability of stereo set to disparity map i.e. P(Y|X) can be expressed as function

Abbrevations used in equations are Matching cost=M.C,Smoothing Cost =S.C,Disparity Map=D.M.

$$Datacost = \prod_{All \ pixels \ \mathbf{S}inD.M} e^{-1*\{M.C \ of \ \mathbf{S} \ given \mathbf{d}_{_}\mathbf{S} \ in \ D.M\}}$$
(3.3)

The value of probability of stereo set to disparity map i.e. (Y/X) is between 0 to 1.

- 1. If matching cost of all pixels is 0, than probability of stereo set to disparity map.i.e. (Y/X) is 1 since \exp^0 is 1
- 2. If matching cost of any pixel is 1, than probability of stereo set to disparity map.i.e. (Y/X) is 0 since \exp^{∞} is 0

Therefore as matching cost of pixels increase, probability of stereo set to disparity map i.i.e. (Y/X) decreases.

3.1.2 Smoothness cost function

The probability of disparity map i.e. P(X) represents total smoothness cost of disparity map. When pixels near each other have the same disparity, smoothness cost i.e. P(X) is 1 and vice versa. Therefore smoothness cost and probability of disparity map are inversely related. The probability of disparity map i.e. (X) can be expressed as a function

$$Datacost = \prod_{\substack{All4connected \ neighbouring pixels \mathbf{S}, \mathbf{t}, in \ D.M.}} e^{-1*\{S.C.between sandtgiven \mathbf{d}_{\mathbf{s}} \ \& \ \mathbf{d}_{\mathbf{t}} \ (3.4)\}$$

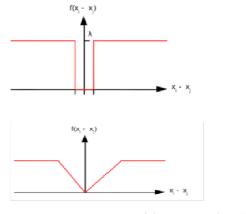
The probability of disparity map i.e. P(X) does not depend on stereo set. The disparity of all pixels in disparity map is constant regardless of any stereo set. The probability of stereo set to disparity map i.e. P(Y|X) and the probability of disparity map i.e. P(X) is expressed as matching cost term and smoothness cost term. The global stereo methods finds disparity map as a minimizing energy function for disparity values. The global stereo methods formulated as an energy minimization which uses data term and smoothes term as objective function.

3.1.3 Models for matching and smoothness cost

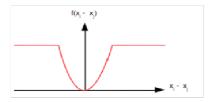
The data cost is based on the intensity differences between the two pixels. The Sum of Absolute Difference (ABS) or Sum of Square Difference (SSD) functions are used as data cost. The smoothness cost or sometimes referred to as the pairwise term which compares adjacent pixels. Most commonly used smoothness cost functions used as smoothness cost models are Pott's model, linear and quadratic models The Pott's model is a binary penalizing function with a single tunable variable. This value controls how much smoothing is applied. The linear and quadratic models have an extra parameter K. K is a truncation value that caps the maximum penalty.

3.2 Markov network

The stereo matching problem can be expressed as markov network. The markov network model is a probability graphical model which consists of undirected graph of 'n' nodes with pair wise potentials as compatibility function.



Truncated linear model $f(n) = \lambda \times \min(|n|, K)$



Truncated quadratic model. $f\left(n\right) = \lambda \times \min(n^2, K)$

Figure 3.1: Pott's model, Linear and Quadratic models

- The state of each nodes 'i' represent as \mathbf{X}_{-} i for given evidence \mathbf{Y} Now, Joint compatibility function for markov network is $\Phi(\mathbf{X}_{-}s, \mathbf{Y})$
- Whereas X_s is hidden node state, Y is evidence or observed state node, Compatibility function for markov network is $\Psi(\mathbf{X}_s, \mathbf{X}_t)$
- If node pair is not compatible, than compatibility between neighboring nodes X_{-s} , X_{-t} is small.
- To find most likely set of nodes $\{X_{-1}, X_{-2}, X_{-n}\}$ for given evidence 'Y' and compatibility between neighboring nodes can be expressed as a joint probability distribution function of n nodes.

$$P(X_{-1}, X_{-2}, X_{-n}/Y) = \prod_{All nodes \mathbf{S}} \Phi(X_{-s}, Y) \prod_{(All neighboring of nodes \mathbf{S}, \mathbf{t})} \Phi(X_{-s}, X_{-t})$$
(3.5)

Now the goal is to find set of nodes that maximizes joint probability distribution.

Now stereo problem is reduce to finding Maximum A Posteriori (MAP) estimation in markov network.

To find Maximum A Posteriori (MAP) estimation in markov network is NP hard means to get a solution for such problem takes unthinkably long time which is because each pixel (node) in disparity map can take any value in disparity space (state).

Graph cuts and Belief Propagation are two global methods used to estimate Maximum a Posteriori (MAP) in reasonable amount of time

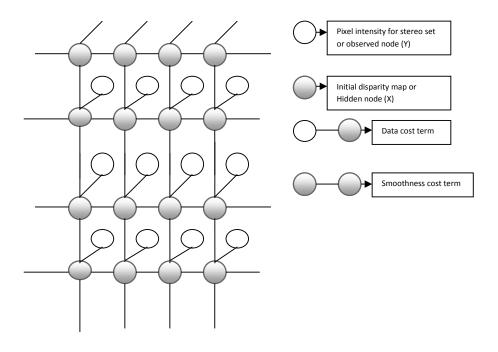


Figure 3.2: Stereo matching problem in Markov Representation

3.3 Belief propagation

The belief propagation algorithm was proposed by Pearl in 1988 for finding exact marginal's on graphs known as trees that contain no loops. The same concepts can be applied to the graphs which contains loops known as Loopy belief propagation.

The Loopy belief propagation is an approximate inference algorithm which keep passing the messages around markov state or node until stable belief state is reached, so the Loopy belief propagation algorithm is an iterative algorithm, messages will converge on doing iterations.

There are three main steps finding Maximum a Posteriori (MAP) estimation or beliefs in markov network.

- 1. Normalization
- 2. Message update or generation
- 3. Finding belief
- 1. **Normalization** is required because while continuously multiplying probabilities, messages becomes zero and hits the floating point limits. The normalization is difference of stereo set (observed node in markov network) to Initial disparity (hidden node in markov network) and divided by 256 for 8 bit brightness or gray level representation.

Table 3.1: Stereo matching problem as probability theory and markov network Comparison of probability theory and Markov network are mentioned in table

| S.No. | Probability Theory | Markov network |
|-------|-----------------------------|---|
| 1 | Maximizing probability of | Maximizing joint probability distribution |
| | disparity map to stereo set | i.e. $P(X_1, X_2, X_n/Y)$ |
| | i.e. $P(X/Y)$ | |
| 2 | Set of pixels in disparity | Markov state |
| | map each with assigned dis- | |
| | parity value | |
| 3 | For given set of stereo im- | For given Evidence Y |
| | ages | |

- 2. In Message updates or generation step messages are updated by joint probability of data cost, smoothness cost and for all incoming messages which are marginalized over given disparity. Initially messages are updated or generated for right movement and similarly for up, left and for down movements. All these four movements of messages in message update step are in sum product approach. The Loopy belief propagation also known as Sum product algorithm.
 - The final message in message update or generation step is a vector and size of the vector depends on disparity value.
- 3. In finding belief step, the values of belief can be found either by Max Product belief propagation or by Minimum of Sum belief propagation.

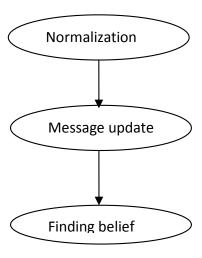


Figure 3.3: Flow chart for Belief Propagation

The best assignment of disparity can be assigned in maximum a posteriori (MAP) by finding largest marginal probability. The belief value in maximum a posteriori (MAP)

at each node or state is maximum marginal.

One of the important assumptions of Max Product belief propagation algorithm is belief values or maximum marginal values at each node or state are different. The belief values are converging by iterating Max Product belief propagation algorithm. The optimal assignment for maximum a posteriori (MAP) is depends on the number of iterations.

Implementation of Belief Propagation

The iterative optimization algorithm is belief propagation algorithm. The steps to implement belief propagation is shown in block diagram shown below

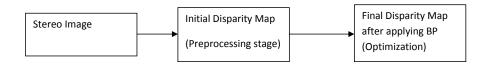


Figure 4.1: Block Diagram for stereo matching technique using Belief Propagation

4.1 Stereo image(Image rectification)

The image rectification is to make the epipolar lines of two camera images aligned horizontally. This can be done by using linear transformations that rotate, translate and skew the camera images.

The principle of image rectification is shown in above figure. The original camera image planes are drawn with solid borders and the rectified image planes are drawn with dashed borders.

Epipolar lines are also drawn from the projected points p and p'to epipoles e and e' After image rectification has been carried out, the epipolar lines of two projected points are parallel and horizontally aligned along the new image planes. The stereo matching problem is therefore reduced to a one dimensional search along horizontal lines instead of a two dimensional search.

Input image referred as a left image corresponding to camera 1, specified in 2-D grayscale. Input image referred as a right image corresponding to camera 2 which is also specified in 2-D gray scale. The Input images left and right must be real, finite, and non sparse. They must be the same class.

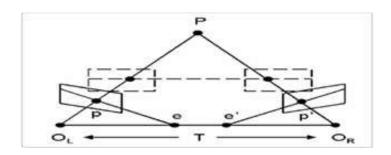


Figure 4.2: Image Rectification

4.2 Initial Depth Map

The initial depth map as a preprocessing stage is generated by two methods

- 1. Matlab in build function(DisparityMap)
- 2. Minimum Index method
- The DisparityMap is a inbuild function in computer vision toolbox of MATLAB. The function DisparityMap finds disparity between left and right images.

The disparity estimation algorithm used for DisparityMap function are Semi global and blockmatching he algorithm. The both disparity estimation algorithm uses the sum of absolute difference(SAD) of each block of pixels for stereo image. Additionally in semiglobal disparity estimation it compares similar disparity on neighboring blocks.

The disparity estimation algorithms also Compute a measure of contrast of the image by using the Sobel filter and Compute the disparity for each pixel in left image.

• In minimum index method sum of absolute difference function is used. The disparity or label is fixed to real number either 8 or 16.

The intensity values of right image is shifted by a label in column wise, than finding the absolute difference between left and right stereo image.

The number of matrix depends on the size of the label or disparity. The next step is finding the minimum shift values as a disparity where minimum occurs

4.2.1 Pseudo code for minimum index method

Left Image =LI of dimension of (M, N)

Right Image =RI of dimension of (M, N)

% label or disparity is 16

% Right image matrix is shifted column wise 1 to 16

```
\label{eq:fori=1:M} \begin{split} &\text{for $j{=}16{:}N$} \\ &\text{E1(i,j)}{=}abs\{LI(i,j){-}RI(i{-}1,j)\}...... \\ &E1(i,j){=}abs\{LI(i,j){-}RI(i{-}16,j)\} \\ &\%\text{The shift value as disparity where the minimum occurs.} \\ &\%\text{This means if the element of E5 (i,j) gets the minimum value among all (E1 to E16)} \\ &(\text{Then the disparity value is 5!)} \text{shift through column index.} \\ &D(i,j){=}\min(E1(i,j){,}E2(i,j){,}E3(i,j){.......}E16(i,j)) \\ &\text{end} \\ &\text{end} \end{split}
```

4.3 Belief Propagation Algorithm

The initial depth map generated either by matlab in build function 'Disparity Map' or by minimum index method is improved by optimization algorithm i.e. Belief Propagation algorithm.

The initial values from initial depth map is normalized between the values 1/16 to 16/16. The messages in belief propagation are updated in one movement. The updated messages in one movement means for the right movement. Similarly the up, left, down movements can be executed to complete one iteration.

4.3.1 The pseudo code for BP

end

```
for i=1: M % in order to avoid the edge effect or index overflow from 16 to M-16
for j=1:N % in order to avoid the edge effect or index overflow from 16 to N-16
DC(i,j)= abs((LI(i,j)-RI(i -D(i,j),j)/ 256;% this will be intensity value difference so we
normalize by dividing by 256
for k=1:16
M(k,1) = \exp{-(DC(i,j) + (abs(D(i-1,j)-(k/16)) + abs(D(i,j+1)-(k/16)) + abs(D(i,j-1)-(k/16)))};
\% here we have taken the values for right movement part of the loopy propagation
% for up movement exp-(DC(i,j)+(abs(D(i-1,j)-(k/16))+abs(D(i+1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-(k/16))+abs(D(i,j-1,j)-
 1)-(k/16))
 % for left movement \exp(DC(i,j)+(abs(D(i+1,j)-(k/16))+abs(D(i,j+1)-(k/16))+abs(D(i,j-1)-(k/16)))
 1)-(k/16))
% for down movement exp-(DC(i,j)+(abs(D(i-1,j)-(k/16))+abs(D(i+1,j)-(k/16))+abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D(i,j+1)-abs(D
 (k/16))
End % this completes the generation of message in the sum of product approach
% Now we need to put the label with the index with maximum value of M.
x=0;
y=0
fork=1: 16
if M(k,1), x
x=M(k,1);
y=k;
end
end% at this point 'y' equals index of the max value of the message vector.
D(i,j) = y/16; % This action is assigning 'the belief' or the max value of the cost.
```

end

4.4 Results and Conclusion

The stereo images for testing are from data sets 2014 of Middlebury computer vision web site (vision.middlebury.edu) Aloe vera plant and Lampshade are considered as test stereo images.

- Stereo image Aloe Vera(427x370)Size of left image :323KB,Size of right image :324KB
- Stereo image Lamp shade(433x370)Size of left image :172KB,Size of right image :172KB

Initial depth map for test images using matlab in build function 'DisparityMap'and than on applying Belief Propagation algorithm are shown



Figure 4.3: Aloe vera left stereo image

Initial depth map for test images using minimum index method and than on applying Belief Propagation algorithm are shown



Figure 4.4: Aloe vera Right stereo image



Figure 4.5: Initial Depth Map using MATLAB Function

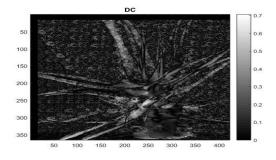


Figure 4.6: Depth Map after BP



Figure 4.7: Lamp shade left stereo image



Figure 4.8: Lamp shade Right stereo image

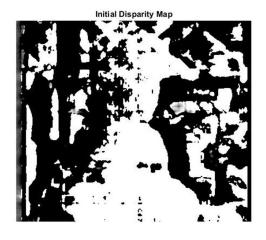


Figure 4.9: Initial Depth MAP using MATLAB Function for Lamp shade

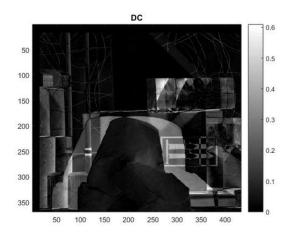


Figure 4.10: Depth Map after BP for Lamp shade

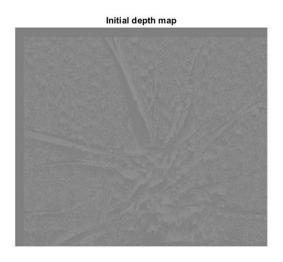


Figure 4.11: Initial Depth Map using Minimum index method for Aloe vera Plant

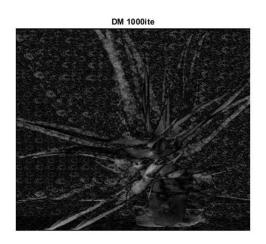


Figure 4.12: Depth Map after BP for Aloe vera Plant

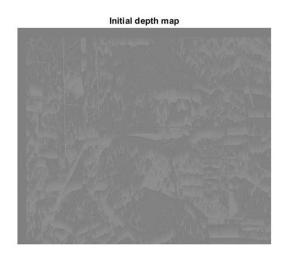


Figure 4.13: Initial Depth Map using Minimum index method for Lamp shade $\,$



Figure 4.14: Depth Map after BP for Lamp shade

Conclusion and Future work

5.1 Conclusion

- Understand the concept related to Markov Random Field and probability theory related to stereo matching algorithm
- Done Literature survey on stereo matching algorithm using iterative Belief Propagation algorithm
- Initial Depth map as a preprocessing stage is implemented using MATLAB in build command 'DisparityMap'from computer vision tool box. The second method Minimum Index Method for Initial Depth Map also implemented.
- The optimization algorithm Belief Propagation for both methods are implemented. The results for both stereo images shows that BP algorithm identifies the objects

5.2 Futre Work

- The Ghost image is present in Initial Depth Map itself, The same ghost image is carry forward after applying Belief propagation algorithm also, In future going to work on this issue
- The BP algorithm can be tested with some natural stereo images or from some other source.

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